USE OF DATA TO INFORM PRACTICE IN

ELEMENTARY SCHOOL CLASSROOMS

by

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STATEMENT OF DISSERTATION APPROVAL

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ABSTRACT

The purpose of this study was to examine the influence of data use on student achievement. Two research questions were considered: is the use of formative assessment tools (Yearly Progress Pro and Acuity) correlated to student achievement outcomes and are there factors (access to computers, a teacher's level of experience, or school level leadership) that explain greater use of formative assessment tools? To answer these questions, a series of hierarchical linear models were used that allowed for factors to be considered at the teacher and school level. While greater use of both formative assessment tools had a positive effect on student achievement for teachers, there was a statistically significant positive effect when Yearly Progress Pro was used more frequently. When considering factors that influence the use of data, teacher experience and access to computers were not found to be statistically significant influences. However, school-level leadership supporting collaboration had a statistically significant positive influence on the frequency of data use. Greater use of formative assessment tools is positively correlated to student achievement; however, further research is required to develop any causal relationship. Additionally, more specific research looking at the effectiveness of various forms of formative assessment in addition to how these assessments are actually utilized by teachers to inform their classroom practice would be beneficial. School-level leadership is also an important component to encourage greater use of formative assessment data, particularly when teacher collaboration around data use is supported by building principals.

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CHAPTER 1

OVERVIEW OF THE STUDY

In the current educational climate focused on standards, accountability, and assessment, there is an increasing demand placed on educators to use data to inform and guide practice. With the passing of the No Child Left Behind (NCLB) Act in 2001, states were required to systematically track the achievement of all students. State-level testing raised the stakes for schools to demonstrate that all students were making "adequate yearly progress" and schools and districts responded with an increased desire to look more carefully at data. Publishing companies also responded to a demand from schools and districts for tools that provide formative assessments so progress toward end of level assessments could be monitored. Improvements in technology coupled with an increase in available formative assessment data have changed the core technology of teaching, emphasizing data-driven decision making as a prominent component. This chapter introduces data-driven decision making frameworks used in educational literature. The purpose of this study to further examine the relationship between data use and student achievement is then outlined as well as the specific research questions and significance of this study in the field of education.

Data-driven decision making is referenced in different ways in current education literature. Data-informed (Schildkamp & Kuiper, 2010, p. 72), data-based (Ingram, Louis, & Schroeder, 2004; Kerr, Marsh, Ikemoto, Darilek, & Barney, 2006), evidence-based practice (Coburn & Talbert, 2006; Honig & Coburn, 2008), or a focus on continuous improvement (Herman & Gribbons, 2001; Ingram, et al., 2004; Lachat &

Smith, 2005) and inquiry (Collinson, Cook, & Conley, 2006; Copland, 2003; Herman & Gribbons, 2001; Wayman, 2005) are all used to describe a process for utilizing data to make informed decisions. Kowalski (2009) viewed data-based decision making as a concept embedded in evidence-based practice and expressed concern that data-based decision making has evolved as a politically charged concept through No Child Left Behind (NCLB). Kowalski stressed, "it has become imperative that administrators and teachers view data-based decision making as a professional responsibility separate from political convictions" (Kowalski, 2009, p. 17).

In whatever manner data-based decision making is referenced, it involves a process in which information informs decisions. The literature concerning this process utilizes organizational learning and management theories. Some of these theories conceptualize the process in a linear manner while others consider the dynamic nature of the process.

Much of the literature on data-driven decision making utilizes organizational learning theories that describe a linear, or cyclic approach to decision making (Blanc, et al., 2010; Breiter & Light, 2006; Halverson, Grigg, Prichett, & Thomas, 2007; Ingram, et al., 2004). Halverson, et al. (2007) developed a framework of data-driven decision making that includes data acquisition, data reflection, program alignment, program design, formative feedback, and test preparation. Using this framework to collect data on practice within schools, they found these processes at work; however, the system was much more organic and seemed to evolve over time rather than having been conceived as a systematic design.

Building on the work of Halverson, et al. (2007), Blanc, et al. (2010) looked at the transformation of benchmark data into knowledge in a movement that progresses from gathering data to identifying problems, trying solutions, and then modifying and assessing their effectiveness. Their study suggests that without this feedback system in place, the data are used superficially, if at all.

Breiter and Light (2006) use a similar conceptual framework that comes from organization and management theory: it builds from data (in a raw form) to information (analyzed and contextualized) and finally knowledge (using information to inform actions). Their six broad steps include collecting, organizing, summarizing, analyzing, synthesizing, and decision making. They found that while the data provide valuable information for conversations, it was important to also recognize the tacit knowledge of teachers (i.e., the information teachers acquire from daily interactions with students through observations and other informal assessments) that is typically not given credibility or consideration in a more systematic approach.

When Ingram et al. (2004) applied concepts of continuous improvement and organizational learning to the data-driven decision-making processes that occur in schools, they found that these rational approaches conflict with how teachers actually operate in schools. In fact, in their longitudinal study of nine high schools implementing continuous improvement approaches, they found when making decisions, approximately 40% of the data used by teachers were systematic, 40% were anecdotal, experience, and intuition, and 15% were a combination of systematic and anecdotal data. Concepts in evidence-based practice would suggest that it is necessary to consider more broadly defined ideas regarding what constitutes evidence and not discount teacher judgment and intuition (Coburn & Talbert, 2006) or what Kowalski (2009) might refer to as professional wisdom.

When focusing on decision making at the classroom level by teachers, it occurs across the feedback system suggested in the work of Halverson, et al. (2007) and Blanc, et al. (2010). Considering data as a resource, the process initiates with inputs to the system and the decisions made at this point determine which resources (curriculum or instructional strategies) a teacher will use. Rather than a linear decision-making model, this study conceptualizes data use as a "dynamic process of interpretation and mutual adjustment that shapes student learning, instructional practice, or policy implementation"(Ball & Forzani, 2007, p. 531). The primary focus of this study is the assumed final outcome of this decision-making process, which is greater gains in student achievement. Teachers who access the data inputs at greater levels engage in this dynamic iterative process as they assess each student's progress, make adjustments, and assess again. In order to engage in this process, teachers must have access to data systems and the ability to use these systems effectively. Figure 1.1 illustrates this dynamic decision-making process using data (Blanc, et al., 2010) and the presumed outcome of student achievement.

A greater focus on data use by teachers in this dynamic process presumably leads to greater gains in student achievement; however, this assumption has not been adequately examined. Prior to 2000, much of the frequent monitoring of student data occurred in special education. The data now available to general education

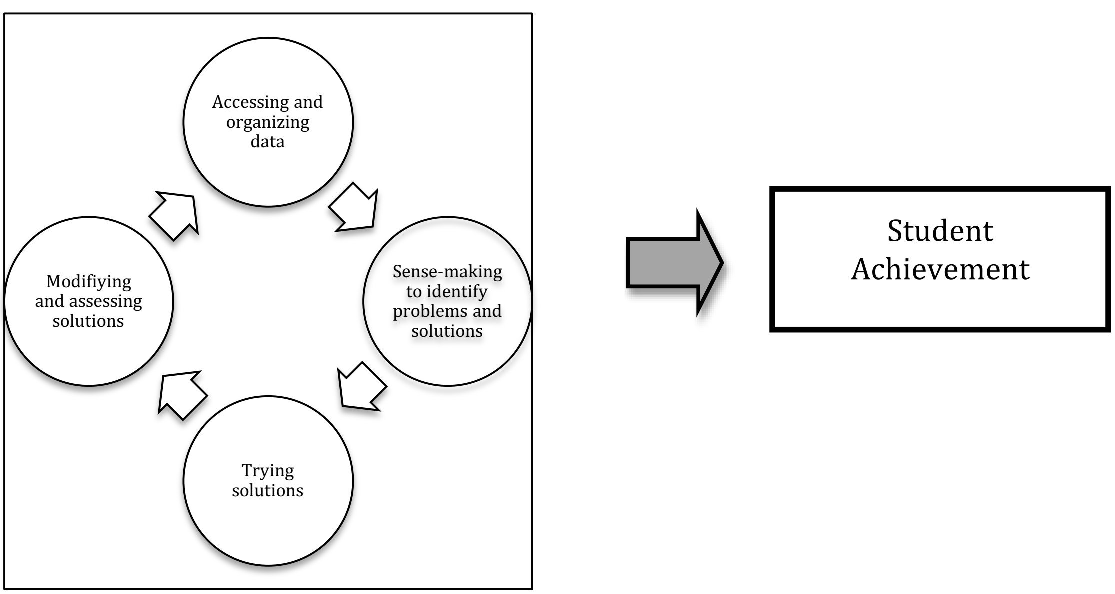

Figure 1.1 Decision-Making Process With Student Achievement Outcome.

teachers include student data from progress monitoring systems similar to those used in special education settings. A few recent studies (Stecker, Fuchs, & Fuchs, 2005; Ysseldyke & Tardrew, 2007) have considered specific curriculum-based measures as formative assessment tools to consider whether their use raises student achievement. Ysseldyke and Tardrew (2007) found that students who participated in progress monitoring gained significantly more than control students in the same school with most significant gains for the lowest performing students based on comparisons of pre to post testing. Stecker, et al. (2005) found that when recommendations for instructional modifications were included in reports to teachers, the resulting student achievement was higher on math computation tests. Another study (Randel, et al., 2011) focused on teacher use of interventions and specific professional development tied to the use of formative data. This study builds on these previous studies to explore the specific link between frequency of use of formative data by general education teachers and end of level student outcome measures. Specifically, this study determines whether teachers who use these types of formative data systems more frequently experience greater increases in the average student achievement in their classrooms. This study also examines which factors explain the level of teachers' data use: access to computers, experience, and school level leadership factors. Figure 1.2 illustrates the conceptual framework for this study linking inputs that may explain greater use of data (based on a review of the literature) to the decision-making process from Blanc, et al. (2000) that ultimately results in greater student achievement.

Teachers have access to a variety of formative data, which are intended to inform their instruction; the assumption is that this information leads to instructional changes with the overall outcome of increased student achievement. Given the costs incurred by districts and states to provide teachers with formative data in an accessible and usable format, it is critical to determine whether greater use of these formative assessment tools

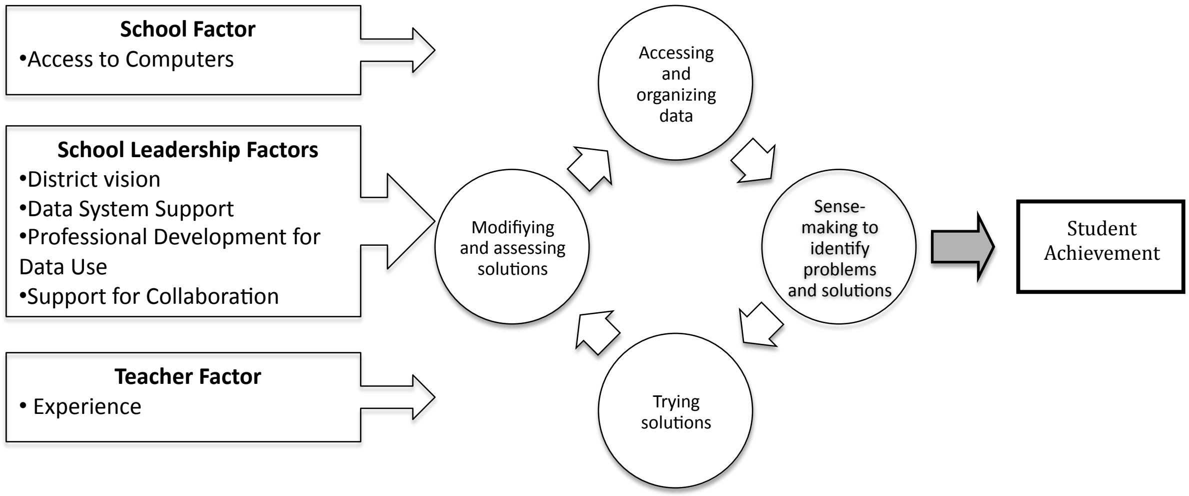

Figure 1.2 Conceptual Framework for Study.

positively influences gains on end of level student achievement measures. It is also essential to determine the strength of the relationship of school-level factors such as access to computers and leadership strategies that influence the extent to which teachers use these tools.

Specifically, this study addresses the following questions:

Is teacher use of formative assessment data positively correlated with average student gain scores for that teacher on state end of level assessments?

Are there school or teacher-level factors that explain greater use of formative assessment tools by teachers?

School districts spend a great deal of money on formative assessment tools in response to the call for greater use of data for decision making. Therefore, it is critical to determine whether greater use of these tools ultimately leads to higher academic achievement for students. School districts should determine the leadership strategies that most effectively lead to greater use of formative assessment tools if indeed their use is significantly correlated with greater student achievement.

Data-driven decision making is the way things should be done in education. As Kowalski (2009) stated, it is a professional responsibility for educators. While previous research focused on the many challenges and frustrations faced by educators as they were asked to use data that were not always immediately accessible or usable, it is critical to look more specifically at how information systems are implemented in a practice wherein teachers are surrounded by data. Is more use of data resulting in better instructional decisions made by teachers and in the end leading to greater increases in student learning?

CHAPTER 2

REVIEW OF THE LITERATURE

This chapter begins with a review of the literature examining the role of data in the process of using available information for the variety of decisions made in education at several levels. Narrowing educational decision making to the classroom level, literature examining the role of formative assessments and curriculum-based measures as data tools is reviewed. There are a few studies that have examined the relationship between increased use of these data sources and the anticipated outcome of greater academic achievement for students and these are also reviewed.

The chapter then focuses on previous studies of data use in education that have helped determine which factors influence data use in schools. While there has been a significant increase in the availability of data systems for use by teachers, some data sources are more likely to be used than others. The importance of professional development and providing time for teachers to collaborate around data analysis are highlighted. Other factors that influence data use include school leadership, teacher experience, and access to data systems. These factors also inform this study and are included in this review.

How Are Data Currently Used in School Systems?

Studies looking across school systems at various data users found that different types of data are used by different stakeholders, and the purposes for which data are used differ relative to one's position (Breiter & Light, 2006; Brunner, et al., 2005; Coburn & Talbert, 2006; Luo, 2008; Marsh, Pane, & Hamilton, 2006; Schildkamp &

Kuiper, 2010). Teachers use data to make decisions regarding lessons and targeting instruction, while administrators use data to allocate resources, set improvement goals, and support conversations (Breiter & Light, 2006; Brunner, et al., 2005; Marsh, et al., 2006; Schildkamp & Kuiper, 2010). Marsh, et al. (2006) found that another common use of data is for identifying “bubble kids.” Seventy-five percent of the administrators surveyed across three states reported that they use data to encourage teachers to focus on “bubble kids” who score just below proficiency in order to increase the likelihood that the school will make adequate yearly progress as required by NCLB.

This use of data as a way to predict performance on end of level high stakes tests, has led to an increase in the demand for formative assessments. Assessment that is used by teachers to provide feedback to adjust instructional practices has been defined as formative assessment (Black & Wiliam, 1998; Clark, 2011; C. Gallagher & Worth, 2008). There is considerable debate regarding whether the assessments themselves ought to be designated as formative or whether their formative nature is determined based on the actions of the teacher. Black and Wiliam (2005) further challenged that the systems to monitor the progress of students that have recently grown in popularity in the United States are not formative assessments at all because results “rarely impact on learning and, as such, might be better described as ‘early-warning summative’” assessments (p. 258). There is also concern that an extreme focus on accountability has the unintended effect of taking time away from more meaningful assessments that would positively influence learning in support of these “early-warning summative” systems. This is consistent with Cohen, Raudenbush, and Ball’s (2003) argument that resources are often added to educational environments with the intent to influence outcomes. However, what influences the outcomes is the *use* of the resources or in this case, how the teacher interacts with the data.

Data Use Linked to Student Achievement Outcomes

Despite the debates over whether assessments are considered formative, Black and Wiliam (1998) reported that when teachers attend to the results of assessments and adjust their instruction, there is an increase in student achievement with effect sizes between 0.4 and 0.7. However, Black and Wiliam (1998) noted that 23 of the 40 studies they considered were gleaned from a meta-analysis conducted in 1986 using primarily "classroom assessment work for children with mild handicaps" (p. 140). There has also been criticism of the Black and Wiliam meta-analysis due to the wide range of assessments included (Randel, et al., 2011) and a general criticism of the poor quality of quantitative data that have been used to support the argument that formative assessment improves academic achievement (Clark, 2011).

More recent studies have considered the uses of formative tools in general education classrooms with the intent to determine the impact on student achievement. One of these studies sought to determine the effectiveness of Classroom Assessment for Student Learning (CASL), a professional development program in formative assessment, to improve student achievement (Randel, et al., 2011). This study, focused on 4^{th}- and 5^{th}-grade teachers of mathematics, used a voluntary sampling method and did not find a significant difference in student achievement in mathematics between the intervention (CASL) and control groups. Another study in 2012 (Faria, et al.) examined classroom-level data-use practices and school-level data-use practices using self reports by teachers and principals in four urban districts. These researchers then analyzed the relationship of these data-use practices and improvements in student achievement in reading and mathematics at grades 4, 5, 7, and 8. Faria, et al. found a positive link between teachers attending to data (independently and collaboratively reviewing their data and responding to the data with changes in instruction) and higher student achievement on end of level tests. They also found a positive relationship between principals engaged in these activities and specific end of level achievement at the elementary level in mathematics.

Other studies seek to find a link between frequent monitoring of student progress and student achievement on long-term goals. The use of curriculum-based assessments (CBM) started in special education in the 1970s and, like formative assessments, has become popular in general education settings since the 1990s (Stecker, et al., 2005). Stecker, et al. (2005) found mixed results in terms of effectively raising student achievement in their study providing CBM results to general education teachers. They did find that students demonstrated greater ability on some mathematics tests in teachers' classrooms where instructional recommendations were provided along with graphical data on the students' progress. Another study conducted by Ysseldyke and Tardrew (2007) specifically looked at the use of Accelerated Math (AM), a Renaissance Learning technology-based product, which allows for tracking of individual student's progress and diagnostic reports for teachers. Ysseldyke and Tardrew randomly assigned 3rd- through 6th-grade teachers to control and experimental groups using a pre-post test design to determine growth in mathematics achievement over a semester. The students of teachers who participated in AM did gain significantly more mathematical skills than the students of teachers in the control classrooms. Additionally, Ysseldyke and Tardrew found variation in the integrity with which the intervention of AM was implemented, which affected the results.

While it seems logical that frequent progress monitoring and corresponding adjustments in instruction ought to lead to greater gains in academic achievement, the use of this type of formative data represents a significant change for teachers. Current practices suggest that the use of currently available data systems and their impact on instruction to ultimately increase student achievement is not integrated into the culture of how teachers have traditionally practiced their craft (L. Gallagher, Means, & Padilla, 2008). The core technology of teaching has significantly changed with pressures of external accountability and "current policy discussions of data-driven decision-making assume that not only more data but virtually all data can be helpful to teachers" (Young & Kim, 2010, p. 27). These additional data sources and the promotion of a variety of products by publishing companies leaves many schools in data overload (Ingram, et al., 2004). With multiple pieces of data available to teachers – from student demographics to frequent assessments providing information on the progress of students relative to end of level outcomes – it is unclear whether or how these data are utilized at the teacher level. Therefore, examining which types of data systems are useful to teachers and whether more access to these data sources ultimately leads to better decisions (i.e., greater levels of student achievement) is critical (Breiter & Light, 2006; Wayman, 2005).

This study seeks to link use of data systems with student achievement in order to more fully develop whether there is a significant relationship. This study builds on the work of Ysseldyke and Tardrew (2007) as well as Stecker, et al. (2005) in order to establish whether the teachers utilizing computer-based formative assessments at greater rates also see greater rates of improved end of level assessment scores.

It is also important to understand what factors contribute to greater data use by teachers. Some research has established a foundation for understanding these factors. The following section reviews some of the data characteristics that have been found to lead to greater data use and some of the issues related to the resistance of teachers toward using data systems. It then highlights studies that have uncovered educator and school factors that seem to support the use of data in schools.

Data Characteristics That Influence Data Use

Data accessibility is one factor that influences data use (Kerr, et al., 2006; Lachat & Smith, 2005; Luo, 2008; Marsh, et al., 2006). In the national surveys conducted by

Gallagher, et al. (2008), a significant increase in access to data was found for teachers as well as administrators. In 2005, 48% of teachers reported having access to student data systems and in 2007, that percentage grew to 74%. Unfortunately, the data they have access to in this study are more likely to be related to grades and attendance, rather than achievement data. Having data readily available is certainly an important component before data can be thoughtfully utilized.

Data quality is another characteristic that influences their use (Kerr, et al., 2006; Lachat & Smith, 2005; Luo, 2008; Marsh, et al., 2006). Marsh, et al. (2006) and Kerr, et al. (2006) both found that data quality is based on the data users' perception of its validity and reliability. For high school principals in Luo's (2008) study, perception of the quality of the data had a direct effect on data use when administrators used it for solving problems in instruction and operations (which was a frequent use), while accessibility to data influenced data use for issues of school vision and collaborative partnerships (found to be a less frequent use of data).

Data must also be available in a timely manner (Kerr, et al., 2006; Marsh, et al., 2006). While Marsh, et al. (2006) found that achievement test scores were the most common form of data used, the authors also pointed out that these data quickly become useless because they typically represent an outcome from a previous year for specific students.

Another characteristic of the data that is important for their utility in education is the format in which they are available (Herman & Gribbons, 2001). Herman and Gribbons (2001) found that educators prefer information in the most simple and self-explanatory manner possible. "[T]eachers and schools had limited tolerance for reading explanatory materials" (Herman & Gribbons, 2001, p. 23). Of course, quality data that are accessible and formatted in a user-friendly manner is not enough. School systems can have plenty of data, but they do not necessarily lead to school improvement

(Schildkamp & Kuiper, 2010) or good decisions (Marsh, et al., 2006). Another important factor is the skill set of the data-users in education. Several educator and school factors are identified in the following section.

Educator and School Factors That Influence Data Use

Research has identified some resistance by teachers to the use of data systems. In addition, teachers' knowledge base of assessment use, their capacity to analyze data, and their ability to adapt instruction influence their use of data to inform instruction.

According to Ingram, et al. (2004), teachers have developed their own measures for evaluating the effectiveness of their teaching and these are often not aligned with data from external sources. Some of these measures include using their experience, intuition and other anecdotal information, but not systematically collected data (despite an expectation from federal mandates of data-driven decision making). Young and Kim's (2010) literature review on formative assessments noted an overall dissatisfaction with published tests by teachers who seem to prefer their own assessments. Because these beliefs and perspectives influence which data sources teachers will use, it is important to look toward whether professional development may have an effect on how data systems are embraced by teachers (Young & Kim, 2010). The Randel, et al. (2011) study specifically utilized a professional development approach as an intervention to determine how this factor influences data use. In their study, while student achievement in mathematics was not significantly impacted, the teachers' knowledge of classroom assessment was significantly higher than the control group following the intervention.

Heritage and Chen (2005) identified five skills needed for effective use of data for school improvement. These are the following: determining what is needed, collecting the required data, analyzing the results, setting goals and priorities, and developing strategies. Several studies point to a lack of these types of skills among school personnel, which limits the effectiveness of data use (Blanc, et al., 2010; Schildkamp & Kuiper, 2010; Volante & Cherubini, 2009). In contrast, having these skills was found to increase the confidence of individuals using data and resulted in a belief in the value of the data by the users (Heritage & Chen, 2005).

Teachers' knowledge of classroom assessment and ability to analyze data is a significant challenge associated with data use. Young and Kim (2010) argued that teachers develop assessment practices only after they enter the classroom. Therefore, teacher experience may also be an important factor and one which Randel, et al. (2011) used as a control variable. In addition to teaching experience, analyzing data requires specific skills for which educators need support (Breiter & Light, 2006; Lachat & Smith, 2005; Marsh, et al., 2006; Symonds, 2004; Wayman, 2005). Breiter and Light (2006) found educators need specific professional development on decision-making that considers the role of data. This is not something with which they are necessarily adept, nor even comfortable doing. Symonds (2004) found that teachers in gap-closing schools received professional development in analyzing test results and linking low performing students to specific instructional strategies.

This ability to link identified needs to appropriate instructional strategies is also a significant challenge influenced by teachers' knowledge of both pedagogy and content. A study conducted by Heritage, Kim, Vendlinski, and Herman (2009) presented teachers with a mathematics performance assessment that they analyzed to make instructional recommendations. They found teachers were able to assess student understanding, but had difficulty using the information to plan for instruction. They concluded "this situation inevitably diminishes the potentially powerful impact of formative assessment on student learning" (p. 31). This conclusion is supported by the results of the study by Stecker, et al. (2005) in which teachers, when provided with instructional recommendations, were able to more significantly impact student achievement. C.

Gallagher and Worth (2008), in their review of formative assessment policies, programs, and practices, also pointed to the need for content knowledge and pedagogical skills in order to use formative assessments effectively.

The educator skills that are important for effective data use include an ability to analyze data, a capacity to use a specific data system, and a level of content and pedagogical knowledge that allows for the appropriate adaptation in instruction to effectively utilize data. Professional development becomes an important factor so that these skills can be addressed and has been identified as an important school-level factor. Other school-level factors identified in the research are collaboration and leadership that support a culture of data use.

Studies have found collaboration is an important element related to effective data use in decision-making (Chrispeels, Castillo, & Brown, 2000; L. Gallagher, et al., 2008; Lachat & Smith, 2005; Schildkamp & Kuiper, 2010; Symonds, 2004; Wayman, 2005). Lachat and Smith (2005) found collaboration to be a key factor impacting data use in low-performing high schools that were making effective efforts at reform. Symonds (2004) also looked at schools that were closing the achievement gap (where low-performing student were making significant progress) and found that teachers in these schools were collaborating around data. Chrispeels, et al. (2000) used a path analysis to determine which variables were most effective in focusing teams on teaching and learning. The most effective variable was the use of data in these teams to identify needs and inform decisions.

School leadership emerged as another important element in schools where data were used effectively (Copland, 2003; Herman & Gribbons, 2001; Lachat & Smith, 2005; Schildkamp & Kuiper, 2010; Symonds, 2004; Wayman, 2005). Leaders committed to using data and providing a supportive data culture are critical. Leadership structures that develop ways to share responsibilities and involve broader school communities are also important factors. In addition, leadership was found to be critical for providing appropriate resources: time for collaboration and professional learning tied to data use (Symonds, 2004).

In a paper presented at the American Educational Research Association annual meeting in 2012, a review of research identified 12 principal strategies that have demonstrated effectiveness in leading data use in schools (Wayman, Spring, Lemke, & Lehr, 2012). These were the following: asking the right questions; communicating expectations about data use; providing data system support; distributing leadership; engaging in personal learning opportunities; ensuring adequate professional learning opportunities; facilitating collaboration around data; focusing data use on a larger context; fostering common understandings of how data use supports teaching and learning; setting goals; modeling data use; and structuring time to use data.

From existing literature, there are factors about data, educators, and schools that determine whether or not data are utilized. Data must be accessible, reliable and valid, timely, and in a format that is user-friendly. Data are more likely to be used if the users have a skills set that includes the ability to analyze the data. Effective teacher collaboration and school-level leadership focused on data use positively influences a school's ability to use data. Professional development and supports for using data are also necessary components for data use to occur. Once the data are analyzed, teachers must determine what action they will take. The next section addresses a significant problem identified in the research: teachers seem to lack knowledge regarding actions to take once information has been gathered.

Instructional Change in Response to Data

Once the data are analyzed and a problem is detected, Marsh, et al. (2006) and Breiter and Light (2006) identified a lack of strategies that teachers could engage to address the issue. Data use to identify the problem is important, but not being able to act on it in meaningful ways is problematic. L. Gallagher, et al. (2008) found that teachers recognized their need for more professional learning around data use, particularly related to how instruction ought to change. Following collaboration around data, there is an assumed action step of adjustment in teaching strategies. However, it is still unknown how or to what extent teachers do adjust their daily practice based on assessment data (Kerr, et al., 2006). Kerr, et al. (2006) also acknowledged that this issue may be related to available resources to provide professional development and assist personnel in developing the level of expertise needed to identify interventions or alternative classroom strategies. While schools have focused attention on collecting data, there has not been equivalent attention given to analyzing data and determining what actions to take as a result of this analysis (Marsh, et al., 2006). Without this piece of the process in place, and without the skills to do this analysis, decision-making that considers data in this dynamic process cannot occur.

There is an assumption that data use leads to a change in instruction. The next assumption is that these changes in instruction (data-based teacher decision-making) lead to positive changes in student achievement. To explore this assumption, Datnow, Park and Wohlstetter (2007) conducted case studies using schools that have demonstrated improvement in student achievement over time. They looked specifically at these schools' approaches to data-driven decision making and found similar strategies in place: a foundation for data-driven decision making, a culture of data use and continuous improvement, user-friendly data management systems with support staff, selecting the right data, building capacity to use data, and analyzing and acting on data to improve performance. Faria, et al. (2012) also explored this assumption looking more specifically at ways in which teachers change their instruction based on data and found that reviewing and responding to interim data at the classroom level can potentially improve student achievement.

Despite much of this research on data-driven decision making, outcomes, such as academic achievement and school improvement, have not been studied in a way that might causally link them to data use (Kerr, et al., 2006). Much of the literature that is cited to support the positive effect of data use on student achievement is from effective schools research that recognizes data use as one of the factors correlated with effective schools (L. Gallagher, et al., 2008). Case studies and formative assessment research has also attempted to establish a link (Black & Wiliam, 1998; Clark, 2011; Randel, et al., 2011). Curriculum-based measures have been used in general classroom settings and appear in current research designed to determine their effectiveness in positively influencing end of level testing (Stecker, et al., 2005; Ysseldyke & Tardrew, 2007).

Policy makers assume that use of data will lead to changes in classroom practice, and researchers are beginning to examine this relationship using more empirical methods. According to Kerr et al. (2006), “[d]espite the increasing focus on data use in practice, research has just begun to investigate whether and how this strategy leads to improvements in teaching and learning” (p. 497). Faria, et al. (2012) found that teachers’ review of data and subsequent instructional changes were the data-related practices most strongly linked to student achievement using survey data from teachers and principals. Datnow, et al. (2007) used a case study approach to identify common features that support use of data in four school systems that were identified as leaders in data-driven decision making as well as having a record of increasing student achievement. While these studies suggest that data use is correlated to student achievement outcomes, what happens as teachers examine data and make instructional changes remains somewhat elusive and has been referred to as the “black box” (Black & Wiliam, 1998).

The focus of this research is investigating whether greater learning occurs in classrooms where teachers more frequently access data resources. This access to data is the initial step in the decision making process at the classroom level. Determining the strength of the relationship between frequency of data use and average gains in student achievement scores is the overall purpose of this study. Teacher and school factors that influence use will be used in the study to determine how these specifically influence data use. Understanding how the factors identified in general data use (accessibility, format, professional development, leadership, etc.) interact with these decisions and how teachers adjust practice will be important as more formative assessments become available. Schools should make informed decisions regarding which formative assessments are worth the investment of their limited resources.

CHAPTER 3

METHODOLOGY

The purpose of this study was to explore the use of formative assessment data by classroom teachers and its relationship to average gains in student achievement scores. The specific research questions addressed by this study were:

1. Is teacher use of formative assessment data in mathematics positively correlated with average student gain scores for that teacher on state end of level mathematics assessments?
2. Are there school- or teacher-level factors that explain greater use of formative assessment tools in mathematics by teachers?

Hierarchical linear modeling (HLM) was used to answer these questions. This is an appropriate model as it allows for an analysis of the influence of the use of formative assessment data by teachers on average gains on end of level assessments at the teacher level while also considering the influences of school-level characteristics (Raudenbush & Bryk, 2002).

This chapter first outlines the data necessary to address these questions, including data collection procedures. The HLM models associated with each research question are explained as well as the manner in which these data were analyzed.

Data

This study focuses on Granite School District. Granite School District is a large geographic district that is spread across central Salt Lake County with 62 elementary schools, 16 junior high schools, and nine high schools in urban and suburban areas. Granite School District is diverse, with a total population of 67,700 students. Sixty-four percent are ethnic minorities and 49% percent qualify for free or reduced lunch.

There are approximately 590 fourth through sixth grade teachers. Fourth through sixth grades participated in high stakes state end of level testing in Utah, which allowed for calculation of student achievement outcome data. Teachers and schools are held accountable for the progress of the students at their schools, based solely on the outcomes of these tests. This study focused on mathematics as a content area in order to narrow the scope of the study. Mathematics represents a content area for which there was formative assessment data available to teachers as well as end of level summative data in order to look at student achievement gain. The data necessary to answer the questions posed in this study include: frequency of access to formative assessment data; student achievement data; and school and teacher factors that influence both student achievement scores and data use.

Teacher Use of Formative Assessment Data

During the 2011-2012 school year, the 4^{th}- through 6^{th}-grade teachers in Granite District had access to formative assessment data in mathematics through two online curriculum-based assessment tools. These two systems were CTB/McGraw-Hill products: *Yearly ProgressPro* (YPP) and *Acuity*.

YPP was a curriculum-based online progress monitoring system aligned to the Utah State Core Curriculum for mathematics. YPP continually assessed mastery of core curriculum mathematics concepts representative of the entire year. The components of YPP included: assessments (both predesigned tests based on the grade level core curriculum as well as customized tests that could be created by teachers from an item bank); instructional resources (exercises that can be assigned to students for additional practice on specific concepts or skills); and reports (these track both individual and class performance over time and across specific skills). Granite School District advised schools to provide computer time for students to take these YPP mathematics assessments at least biweekly throughout the year in preparation for end of level criterion referenced tests.

Acuity was a benchmark online assessment system, which determined students' mastery of the core curriculum mathematics content and skills. There were four benchmarks tests that could be given as a pre- and postassessment at regular intervals throughout the year. The four tests assessed different concepts that were taught during these four intervals (based on district curriculum maps) and in total comprised the entire mathematics curriculum for the year. In addition to predesigned tests, the *Acuity* system offered teachers the ability to create custom tests to assess a specific skill or concept. *Acuity* also had instructional resources (exercises that can be used to re-teach concepts or skills) and reports (individual and class reports as well as item analysis reports). Granite School District advised schools to provide computer time for students to take the *Acuity* mathematics pre- and posttests at four intervals throughout the year.

YPP and *Acuity* were both available to teachers as formative assessment tools given that teachers use them for instructional decision making. Although Granite School District advised specific use of these two tools, teachers used these online assessments in varying degrees. The amount of data use for each teacher in this study was measured based on the *number of curriculum-based tests given* in mathematics in YPP and the *number of tests given* in *Acuity* for the 2011-2012 school year. This measure is limited to the frequency of use and not how these data were used by teachers. These data were collected for each individual teacher using district-wide data available through Granite District's Research and Assessment Department.

During the 2012-2013 school year, only *Acuity* was available to teachers. *Acuity* had both benchmark and screener tests. Teachers were instructed to give a pre and post assessment to measure progress on four benchmark assessments during the school year. The screener test was to be given three times during the school year assessing each student's progress on the curriculum for the entire school year.

Student Achievement Data

The student achievement variable for the 2011-2012 school year was measured at the teacher level using a "Progress Score" calculated by quantifying the students' growth on Utah Criterion Referenced Test (CRT) for mathematics. Each teacher's progress score was calculated by comparing each student's performance on the end of level CRT with that student's previous year's performance. Points were awarded based on the student's movement from one level of proficiency (as determined by the Utah State Office of Education) to another level. For example, a student who scored at a Level 1a in year one and then scored at a Level 2a in year two would generate 350 points for the teacher (based on the values in Table 3.1). The progress score for each teacher is calculated by dividing the total number of points for the teacher by the number of students for which

Table 3.1

Progress Scores Calculation

	Year 2 Level					
Year 1 Level	1a	1b	2a	2b	3	4
1a	0	200	350	350	400	400
1b	0	125	225	350	375	400
2a	0	50	150	225	350	350
2b	0	0	75	175	275	325
3	0	0	0	100	200	275
4	0	0	0	0	125	225

there are matched data (*A Guide to U-PASS Determinations*, 2008). Each teacher's progress score is available through *Data Display*, a state-wide online system, and was used as a continuous variable.

Factors That Influence Student Achievement

To control for other factors that may influence student achievement outcomes, other school-level data were considered. District-wide data were available to determine the following for each school: socio-economic status, measured by percentage of students who qualify for free or reduced lunch (FRL); English language learner (ELL) population, measured by percentage of students identified as ELL; students who qualify for special education services, measured by the percentage of students with disabilities (SWD) at each school; and ethnic minority population (ETH), as measured by the percentage of students who are of an ethnicity other than Caucasian. These factors were considered in the models as control variables in order to determine what role data use has on student achievement independent of other factors that influence academic achievement.

Factors that Influence Data Use

School factors that have been identified in the literature as influencing data use were considered in order to answer the second research question. Since the formative assessment tools are available on-line, the availability of technology is an important factor. Access to computers for this study was measured based on the ratio of students to computers designated for student use in each school. This information was available through Granite District's Technology Department.

Other important factors found in schools that use data at high rates are school leadership factors, including a clear district vision for data use, data system supports, supports for using data, and leadership strategies that encourage data use through engaging in personal learning opportunities as a building administrator, ensuring adequate professional learning opportunities in the school, facilitating collaboration around data, fostering common understandings around data use, goal-setting, and structuring time to use data (Lachat & Smith, 2005; Wayman, Cho, Jimerson, & Spikes, 2012). A survey of building administrators (Appendix) was used to determine the degree these school leadership factors were present in each school. The survey was based on a data use measure developed by Wayman, et al. (2007) for their district-wide evaluation of effective leadership strategies influencing the use of data to inform practice in Natrona School District and effective principal leadership strategies (Wayman, Spring, et al., 2012). The constructs and alpha reliabilities reported by Wayman, et al. (2007) were District Vision (0.831), Supportive Computer Systems (0.833), and Supports for Using Data (0.834). The items used for these constructs were adapted to be specific to Acuity as an assessment tool. The construct, Supports for Collaboration Around Data Use, included items adapted from a study by Wayman, et al. (2012) identifying strategies principals use to facilitate teacher data use. Each item was responded to on a 5-point Likert-type scale: strongly disagree, somewhat disagree, neither disagree no agree, somewhat agree, or strongly agree. An overall total leadership score was generated as a sum of each item to be used as a single variable. Each construct was also considered using the average score for the items in that construct. This survey was sent out electronically to the 62 elementary school administrators in Granite School District in the fall of 2012. Fifty administrators responded and of those, 32 were still at the same school where they had been for the 2011-2012 school year. The survey questions asked about data use regarding Acuity only, because YPP was not being used during the 2012-2013 school year.

A teacher-level factor that may influence use of data is the number of years of teaching experience. The number of years of experience was collected through access to information available from Granite District's Human Resource Department and was calculated as a categorical variable. In order to delineate between new teachers, those with some experience, and those who had been in the profession a significant amount of time the categories used were 0-3 years, 3-7 years, 7-15 years, 15-24 years, and over 25 years.

Method

A set of hierarchical linear models (HLM) was used after preparing the data using the statistical software SPSS. This analysis allows for separation of the within-school variation of student achievement that may be explained by the data-use factors of teachers from the between-school variation that may be explained more by the school's socio-economic status, English Language Learner population, percentage of students with disabilities, or percentage of ethnic minority students. HLM also allows for the placement of multiple factors in models and when these effects are set as random, it is possible to estimate the variance of those effects as well as their covariance (Hayes, 2006). The two research questions are considered along with the models used to analyze the data.

Question 1: Is teacher use of on-line assessment tools positively correlated with student achievement on state end of level assessments? This question was answered using the following level 1 model:

Level 1 $$Y_{ij} = \beta_{oj} + \beta_{1j}(YPPUSE_{ij}) + \beta_{2j}(ACUUSE_{ij}) + r_{ij} \quad (3.1)$$

This model expresses teacher *i*'s progress score (the dependent variable) as a function of YPP data use and Acuity data use (the independent variables) unique to school. The coefficients (β_{Ij} and β_{2j}) describe the strength and direction of the influence each of these independent variables has on the dependent variable. β_{oj} is the school mean, while r_{ij} is the residual.

To control for other variables that may also influence the student achievement variable, school-level factors were considered. These included demographic factors: percentage of students on free or reduced lunch (FRL), the percentage of students who were English Language Learners (ELL), the percentage of students who have disabilities (SWD), and the percentage of students who were represented ethnicities other than Caucasian (ETH). These factors were added in the following level 2 means-as-outcomes model:

Level 2 $$\beta_{0j} = \gamma_{00} + \gamma_{01}(FRL)_{1j} + \gamma_{02}(ELL)_{1j} + \gamma_{03}(SWD)_{1j} + \gamma_{04}(ETH)_{1j} + u_{0j} \qquad (3.2)$$

Question 2: Are there school- (access to computers, school leadership factors) or teacher- (number of years of experience) level factors that explain greater use of these assessment tools by teachers?

This question was answered using two different sets of models because the leadership variables were only available for some of the schools. The first set looked specifically at the use of formative assessment tools (YPP and Acuity) as the dependent variable and teacher experience as the independent variable. Access to computers was added at the school level to consider this variable as well. Another set of models was used to look specifically at the role of leadership at the school level. These models used the progress score again as the dependent variable, but included a smaller data set.

In order to determine the influence of teacher experience (TEXP) on the use of these assessments, models were used considering YPP and Acuity use as the dependent variable and the number of years of teacher experience as the independent variable. Computer access (COMACC) was added as a school variable at level 2. This was measured based on the ratio of students to computers at each school. These variables were available for the 2011-2012 school year and the following models were used:

Level 1 $$Y(\text{YPPUSE or ACUUSE})_{ij} = \beta_{0j} + \beta_{1j}(\text{TEXP}_{ij}) + r_{ij} \quad (3.3)$$

Level 2 $$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{COMACC})_j + u_{0j} \quad (3.4)$$

In order to consider school leadership factors (LS), a set of different models were used because the data available for the leadership variable was limited to principals who responded to the survey and those who were also at the same school during the 2011-2012 school year as well in December of 2012 when the survey was conducted. These models only included Acuity use because the survey questions were limited to the Acuity data system (given that YPP was not used during the 2012-2013 school year). These models built on the model for the first question using the Progress Score as the outcome variable and adding demographic data at the second level as well as leadership factors.

Level 1 $$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{ACUUSE}_{ij}) + r_{ij} \quad (3.9)$$

Level 2 $$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{FRL})_{1j} + \gamma_{02}(\text{ELL})_{1j} + \gamma_{03}(\text{SWD})_{1j} + \gamma_{04}(\text{ETH})_{1j} + u_{0j} \quad (3.10)$$
$$\beta_{1j} = \gamma_{10} + \gamma_{11}(\text{LS})_j + u_{1j} \quad (3.11)$$

In addition to the single leadership variable, separate constructs were also considered. These constructs were District Vision (DV), Supportive Computer Systems (CS), Supports for Using Data (SupD), and Supports for Collaboration around data use (SupC). The following model was used to determine if one of these separate leadership factors had a greater influence than others.

Level 1 $$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{ACUUSE}_{ij}) + r_{ij} \quad (3.12)$$

Level 2 $$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{FRL})_{1j} + \gamma_{02}(\text{ELL})_{1j} + \gamma_{03}(\text{SWD})_{1j} + \gamma_{04}(\text{ETH})_{1j} + u_{0j} \quad (3.13)$$
$$\beta_{1j} = \gamma_{10} + \gamma_{11}(\text{DV})_j + \gamma_{12}(\text{CS})_j + \gamma_{13}(\text{SupD})_j + \gamma_{14}(\text{SupC})_j\, u_{1j} \quad (3.14)$$

CHAPTER 4

RESULTS

The purpose of this study was to explore the use of formative assessment data by classroom teachers and its relationship to average gains in student achievement scores. Specifically, the initial question was to determine whether teachers who more frequently have students use a formative assessment tool in mathematics have greater student achievement success as measured by each teacher's progress score, which quantifies that teacher's ability to move students between outcome levels on an end of year assessment. Secondly, the study looked for the strength of the relationship of frequency of data use by teachers with their access to computers, school leadership factors, and their level of teaching experience.

Use of Assessment Tools Correlated to Student Achievement

Using data from the 2011-2012 school year, the first question included 524 4th- through 6th-grade teachers in Granite School District. The variables and descriptions for these teachers are displayed in Table 4.1. The number of years of teacher experience varied from 1 to 45 years. This variable was considered as a categorical variable with 0 – 3 years (1), 4 -7 years (2), 8 - 15 (3), 16 -24 (4), 25 or more years (5) used as categories. As mentioned previously, these categories allow for the consideration of levels of experience from new teachers to those who have been in the profession for a significant amount of time.

Table 4.1

Variables and Descriptions, Teachers (2011-2012)

Teacher level *N*=524	Description	Mean	*SD*	Min.	Max.
TEXP	Years of service, Categories (1= 0-3; 2 = 4-7; 3 = 8-15; 4 = 16-24; 5 = 25 or more)	3.16	1.25	1	5
YPPUSE	Number of tests given by teacher	20.05	20.04	0	247
ACUUSE	Number of tests given by teacher	6.43	2.10	0	25
Progress Scores	Continuous variable calculated based on teacher's movement of students from one proficiency level to another	197.90	38.16	82	298

Use of mathematics formative assessment was measured based on the number of assessments given per student using two separate computer-based assessment tools: Yearly Progress Pro (YPP) and Acuity. The number of tests varied from 0 to 247 for YPP and from 0 to 25 for Acuity. The mean number of tests given in Acuity was 6.43, with a relatively small standard deviation of 2.1. This indicated very little variation in this variable. End of level mathematics achievement was measured for each teacher using a progress score calculated by comparing each student's performance on the end of level CRT with that student's previous year's performance. Points were awarded based on the student's movement from one level of proficiency (as determined by the Utah State Office of Education) to another level. The progress scores for each teacher varied from 82 to 298. These descriptive results are listed in Table 4.1.

There were 62 schools included in the study. Factors that may influence progress scores at these schools were considered and are displayed in Table 4.2. These included the percent of ethnic minority students, English language learner students, special education students, and free or reduced lunch qualified students. The percentages of ethnic minority students varied from 5.8 to 81; the percentages of English language learners varied from 0.8 to 72.8; the percentages of students with disabilities (special

Table 4.2

Variables and Descriptions, Schools (2011-2012)

School level *N*=62	Description	Mean	*SD*	Min.	Max.
ETH	% Ethnic Minority	44.52	20.35	5.8	81
ELL	% English Language Learners	30.18	17.55	0.8	72.8
SWD	% Students With Disabilities	16.26	4.24	7.1	28.5
FRL	% Free or Reduced Lunch	53.73	22.56	4.3	92.8
COMACC	Ratio of students per computer	2.96	1.19	1.3	7.7

education students) varied from 7.1 to 28.5; and the percentages of students qualifying for free or reduced lunch varied from 4.3 to 92.8. Computer availability at each school was considered as a factor that may influence the amount of data use by teacher in order to answer question 2. This variable was measured as a ratio of students per computer and varied from 1.3 to 7.7. These school descriptors are displayed in Table 4.2.

A series of hierarchical linear models was used to statistically analyze whether a teacher's use of formative assessment data in mathematics is positively correlated with average student gain scores for that teacher on end of level mathematics assessments (progress score). An initial null model (Table 4.3) using intercepts-only with teacher progress score as the outcome variable revealed an intraclass correlation (ICC) of 0.12 indicating that 12% of the variance in the progress scores was at the school level and 88% of the variance occurred at the teacher level.

To determine the influence of data use, the teacher variables of YPP and Acuity use were considered at level 1 (Table 4.4). YPP use was added as a predictor variable for the outcome variable of progress score and the resulting regression coefficient was positive and statistically significant (b=0.35, p<.001). The greater the use of YPP by a teacher, the higher the progress score (Model 1). In this model, 3% of the variance in progress score could be attributed to YPP use. In the next model (Model 2), Acuity was

Table 4.3

Results From Null Model, Progress Score as Outcome

Fixed Effect		*Coefficient*	*SE*
Progress Score, γ_{00}		197.99	2.24
Random Effect	*Variance Component*	*df*	χ^2
Progress Score, u_{0j}	177.79	61	141.26
Level -1 effect, r_{ij}	1283.42		

added as a predictor variable and the resulting regression coefficient was positive, but not statistically significant (*b*=1.09, *p*=0.315). Acuity use could explain 8% of the variance in the progress score. When both YPP and Acuity were added as predictor variables (Model 3), this explained variance increased to 10% and the resulting coefficients were similar, indicating that both have a positive effect on the progress score, but YPP use is statistically significant ($p<.001$).

School variables (ethnic minority percentage, English Language Learner percentage, students with disabilities percentage, and free or reduced lunch percentage) were considered using a means-as-outcomes model with these as level 2 predictor variables (Model 4 in Table 4.4). These school variables explained 33% of the variance in progress scores. The resulting regression coefficient for the percentage of ethnic minorities was negative and statistically significant (*b*=-1.21, $p<0.05$), while the regression coefficient for the percentage of English Language Learners (ELL) was positive and statistically significant (*b*=1.39, $p<0.01$). These indicate that the higher the percentage of ELL students at a school, the higher the progress scores; but, the higher the percentage of ethnic minority students, the lower the progress scores. The final model (Model 5) considers all variables in the model. In this model, 10% of the Level 1 variance is explained by YPP and Acuity use, while 25% of the variance is explained by the demographic variables. These results are shown in Table 4.4.

Table 4.4

HLM Results: Progress Score as Outcome

	Model 1	Model 2	Model 3	Model 4	Model 5
Level 1					
Intercept	197.98 (2.24)***	197.99 (2.24)***	197.99(2.24)***	197.96 (1.96)***	197.97(1.96)***
YPP	0.35 (0.08)***		0.31(0.09)***		0.32(0.09)***
Acuity		1.09 (1.07)	0.72 (1.06)		0.71(1.06)
Level 2					
ETH				-1.21 (0.55)*	-1.23 (0.55)*
ELL				1.39 (0.54)**	1.41 (0.54)**
SWD				-0.58 (0.53)	-0.62 (0.54)
FRL				-0.23 (0.29)	-0.23 (0.29)
Variance (null)					
Level 1 (1283.42)	1248.65	1180.04	1153.76	1281.85	1152.39
Level 2 (177.79)	181.51	189.08	191.8	118.92	132.57
Variance Explained compared to Null					
Level 1	0.03	0.08	0.10	-	0.10
Level 2	-	-	-	0.33	0.25

* $p < .05$; ** $p < 0.01$; *** $p < .001$

School and Teacher Factors That Explain Use of Assessment Tools

To answer the second question, access to computers and leadership variables were considered at the school level and teacher experience was considered as a teacher variable. This question was answered by two different sets of models. The first set considers computer access at the school level and teacher experience at the teacher level using the full data set of 524 teachers and 62 schools. The second set considers leadership variables at the school level with a smaller set of the data (32 schools) because the leadership variable was not available for all schools.

Teacher Experience and Computer Access

HLM was used to statistically analyze whether a teacher's years of experience and access to computers at each school influenced the frequency of data use using YPP and Acuity use as the outcome variable. The null models for both YPP and Acuity are shown in Table 4.5. The null model resulted in an ICC of .29, meaning that 29% of the variance in the YPP use occurs at the group level, while 71% occurs at the individual level. The null model with Acuity use as an outcome resulted in an ICC of .09 meaning that 9% of the variance in Acuity use occurs at the group level and 91% at the individual level.

YPP use was used in the first two models considering the variable of teacher's years of experience at Level 1 and access to computers at Level 2 (Table 4.6). Teacher experience explained 8% of the variance in YPP use. The resulting coefficient was negative (b=-0.31) and not statistically significant. When computer use was added at level 2, it did not help explain any of the variance in use of YPP. The resulting coefficient was negative (b=-2.04) and also not statistically significant.

Acuity use was considered with the next two models (Table 4.7). With teacher experience added at level 1, 13% of the variance in use of Acuity was explained compared

Table 4.5

Results From Null Models, YPP, and Acuity as Outcomes

Fixed Effect		*Coefficient*	*SE*
YPPUSE, γ_{oo}		19.96	1.53
Random Effect	*Variance Component*	*df*	χ^2
YPPUSE, u_{oj}	116.33	61	292.45
Level -1 effect, r_{ij}	288.99		

Fixed Effect		*Coefficient*	*SE*
ACUUSE, γ_{oo}		6.42	0.12
Random Effect	*Variance Component*	*df*	χ^2
ACUUSE, u_{oj}	0.41	61	120.71
Level -1 effect, r_{ij}	4.02		

Table 4.6

HLM Results for YPP as Outcome

	Model 1	Model 2
Level 1 (*n*=524)		
Intercept	19.81(1.67)***	19.81(1.63)***
TEXP	-0.31(0.46)	-0.30 (0.46)
Level 2 (*n*=62)		
COMACC		-2.04(1.24)
Variance (null)		
Level 1 (288.99)	267.06	266.96
Level 2 (116.33)	140.20	137.57
Variance Explained Compared to Null		
Level 1	0.08	0.08
Level 2		-0.18

* $p < .05$; ** $p < 0.01$; *** $p<.001$

Table 4.7

HLM Results for Acuity as Outcome

	Model 1	Model 2
Level 1 (*n*=524)		
Intercept	6.38 (0.11)***	6.38(0.11)***
TEXP	0.11 (0.07)	0.11 (0.07)
Level 2 (*n*=62)		
COMACC		-0.01(0.07)
Variance (null)		
Level 1 (4.02)	3.50	3.50
Level 2 (0.41)	0.34	0.35
Variance Explained Compared to Null		
Level 1	0.13	0.13
Level 2		0.15

* $p < .05$; ** $p < 0.01$; *** $p<.001$

to the null model. In this model, the resulting coefficient was slightly positive (b=0.11), but not significant. Adding computer access at level 2, 15% of the variance in Acuity use was explained. The coefficient for computer access was negative (b=-0.01), but also not statistically significant.

Leadership Variables

In order to explore the influence of leadership factors on data use, an administrator survey (Appendix) was administered online in December of 2012. Fifty administrators responded to the survey. The variables and descriptions of these leadership factors are provided in Table 4.8. An overall leadership score was generated from 16 statements that building principals were asked to respond to with their level of agreement on a 5-point Likert-type scale. The mean leadership score was 58.14 with a standard deviation of 7.63. The statements were grouped by constructs: District Vision, Supportive Computer Systems, Supports for Using Data, and Supports for Collaboration Around Data Use. Each construct was considered using the average score for the items in

Table 4.8

Variables and Descriptions of Leadership, Schools (December, 2012)

School level *N*=50	Description	Mean	*SD*	Min.	Max.
LS	Total of all responses on Administrator Survey	58.14	7.63	39	75
DV	District Vision Construct (mean score of items within this construct)	4.43	0.70	1.5	5.0
CS	Supportive Computer Systems Construct (mean score of items within this construct)	3.34	0.85	1.25	5.0
SupD	Support for Using Data Construct (mean score of items within this construct)	3.59	0.70	2	4.67
SupC	Support for Collaboration Construct (mean score of items within this construct)	3.63	0.61	2	5.0

that construct. The district vision construct had the highest mean score, while supportive computer systems had the lowest mean score. Each construct had a similar deviation around the mean.

Although 50 elementary school principals responded to the survey, it was not given until December of 2012. Therefore, it was necessary to determine which of these principals were also serving as a principal at their respective school during the 2011-2012 school year when the information on data use with Acuity and YPP was collected. Of the 50 administrators who responded to the survey, 32 were at the same school during the 2011-12 school year. In order to determine whether these 32 principal responses were similar to the entire set of 50, the mean and standard deviation were calculated, and a *t*-test value was generated. These results are displayed in Table 4.9. The mean scores and their deviations were similar and none of the *t*-test values were significant. Therefore, the 32 principals who remained at their respective schools in December of 2012 were

Table 4.9

Leadership Variables, Comparing Subset

	All Survey Responses (*n*=50)	Subset (*n*=32)		
	Mean (*SD*)	Mean (*SD*)	Mean Difference	*t*-test value
LS	58.14(7.63)	59.47(6.33)	-1.33	-0.86
DV	4.43(0.70)	4.41(0.81)	0.02	0.12
CS	3.34(0.85)	3.54(0.77)	-0.2	-1.10
SupD	3.59(0.70)	3.63(0.68)	-0.04	-0.26
SupC	3.63(0.61)	3.66(0.51)	-0.03	-0.24

* $p < .05$; ** $p < 0.01$; *** $p<.001$

determined to be statistically similar with regard to these variables as those who were at different schools in 2012.

The 32 schools used to analyze the influence of leadership factors on data use were also compared to the entire set of 62 schools used for the previous analyses on the other school level factors considered in this study. Table 4.10 displays this comparison of ethnic minority percentage, English language learner percentage, students with disabilities percentage, and free or reduced lunch percentage. The means were compared and a *t*-test was calculated for these factors. None of the variables were significantly different and therefore, the 32 schools were similar to the entire set of 62 schools with regard to these demographic variables.

Table 4.10

School Variables, Comparing Subset

	All Schools (*n*=62)	Subset (*n*=32)		
	Mean (*SD*)	Mean (*SD*)	Mean Difference	*t*-test value
ETH	44.52(20.35)	41.04 (18.46)	3.48	0.84
ELL	30.18(17.55)	27.02(15.36)	3.16	0.90
SWD	16.26(4.24)	16.82(4.41)	0.56	-0.59
FRL	53.73(22.56)	52.70(19.93)	1.03	0.23

* $p < .05$; ** $p < 0.01$; *** $p<.001$

Using data from these 32 schools, HLM was used to statistically analyze the influence of leadership factors while continuing to control for school demographic variables. The models used only include Acuity use as a level 1 variable because the administrative survey was specific to this formative assessment tool (YPP was no longer in use within Granite School District during the 2012-2013 school year). The null model (Table 4.11) resulted in an ICC of 0.07, meaning that 7% of the variance in the progress score occurred at the school level and 93% at the individual teacher level.

The models displayed in Table 4.12 consider Acuity use as a level 1 variable and then add level 2 predictor variables (ethnic minority percentage, English Language Learner percentage, students with disability percentage, and free or reduced lunch percentage) to determine their influence on the progress score. When compared to the null model, these school variables explained 86% of the variance in progress scores. The resulting regression coefficient for the percentage of ethnic minorities was negative and statistically significant (b=-3.33, p<0.001), while the regression coefficient for the percentage of English Language Learners (ELL) was positive and statistically significant (b=3.13, p<0.001). When these school variables were controlled for in regard to their influence on progress scores, the influence of Acuity use on the progress scores became statistically significant (p<0.05). The next model (Model 3) considered the influence of

Table 4.11

Results from Null Model, Progress Score as Outcome

Fixed Effect		*Coefficient*	*SE*
Progress Score, γ_{oo}		199.59	2.72
Random Effect	*Variance Component*	*df*	χ^2
Progress Score, u_{oj}	103.51	31	54.00
Level -1 effect, r_{ij}	1303.85		

Table 4.12

HLM Results With Leadership Variables, Progress Score as Outcome

	Model 1	Model 2	Model 3	Model 4
Level 1 (*n*=302)				
Intercept	199.52(2.65)***	199.83(2.02)***	199.73(1.96)***	199.69(1.92)***
ACUUSE	1.84(1.01)	1.62 (1.08)	2.17(1.03)*	2.26 (1.03)*
Level 2 (*n*=32)				
ETH		-3.33(0.82)***	-3.39 (0.81)***	-3.30 (0.80)***
ELL		3.13(0.88)***	3.14 (0.87)***	3.08 (0.86)**
SWD		-0.46(0.53)	-0.49 (0.50)	-0.48 (0.50)
FRL		0.50(0.37)	0.54 (0.35)	0.50 (0.35)
ACUUSE SLOPE				
LS			0.34 (0.11)**	
DV				1.82 (1.1)
CS				2.34 (1.82)
SupD				-0.56 (1.52)
SupC				2.69 (1.18)*
Variance (null)				
Level 1 (1303.85)	1300.45	1302.50	1301.34	1306.40
Level 2 (103.51)	92.89	14.84	6.76	5.60
Variance Explained compared to Null				
Level 1				
Level 2	0.10	0.86	0.93	0.95

* $p < .05$; ** $p < 0.01$; *** $p < .001$

the leadership variables on Acuity use as a slope-as-outcome model while controlling for the influence of the school-level variables (ethnic minority percentage, English Language Learner percentage, students with disability percentage, and free or reduced lunch percentage) on the progress score. In this model, the coefficient for the leadership total was positive and statistically significant (b=0.34, p<0.01). A final model (Model 4) was used to determine which aspects of leadership were most significant in terms of the influence on Acuity use. In this model, support for collaboration had a positive and statistically significant effect on Acuity use when controlling for the other school level variables (b=2.69, p<0.05). Additionally, the use of Acuity continued to have a positive influence on the progress score at a statistically significant level (b=2.26, p<0.05). The explained variance for level 2 with all variables in the model was also very high at 95%, as shown in Table 4.12.

CHAPTER 5

SUMMARY AND IMPLICATION OF FINDINGS

The present study and the analysis of the resulting data was beneficial in providing insight into the use of formative assessment data at the classroom level and its influence on student achievement end of level outcomes in mathematics. This study was also beneficial in its look at leadership factors at a school level as well as teacher-level factors that influence the frequency of data use by teachers and the resulting influence on end of level assessments. This chapter will provide a summary of these results as well as discuss limitations of this study and implications for further research and implications for practice.

Summary of Results

This study sought to link teacher use of formative assessment data to specific end of level outcomes in student achievement. When YPP and Acuity use were considered (based on total tests given by individual teachers), they were both found to have a positive effect on the progress score of that teacher. YPP use was statistically significant ($p<.001$) in its influence on a teacher's progress score; the more these teachers had their students use YPP, the greater their progress scores in mathematics. YPP had a greater disparity of scores around the mean of 20 tests given (standard deviation was 20) compared to Acuity with a mean of 6.43 and a standard deviation of 2.1. The greater variation in YPP scores may also explain why the influence on progress scores was able to be determined in the models used as compared to the small variation in the Acuity use scores. Acuity was used more specifically as a benchmarking tool for teachers to determine how students were performing between pre- and posttesting at specified time periods throughout the school year. Additionally, there was a district directive to give the Acuity tests at these prescribed intervals. YPP was utilized more as a progress monitoring tool and while there was an early district directive to use this tool at specified times, this directive changed during the 2011-2012 school year in response to concerns from teachers that too many assessments were required. YPP also had a greater capacity to allow for teacher to individually create and use this tool for formative assessments as compared to Acuity, which functioned more as a benchmarking tool.

When considering the influences of the use of formative assessment on end of level outcomes, HLM analysis allowed for the control of other variables that also influenced teacher progress scores. The school-level variables considered in this study were the percentage of students from ethnic minorities, percentage of English Language Learners, percentage of students with disabilities, and percentage of students who qualified for free or reduced lunch. These school variables explained 33% of the progress score. However, when progress scores were analyzed, 88% of the variance in a teacher progress score occurred at the individual level and just 12% was at the school level. Interestingly the percentage of English Language Learners had a positive effect on the progress scores of the teachers at a statistically significant level ($p<0.01$) and the percentage of students from ethnic minorities in a school had a negative influence on the teachers' progress scores ($p<0.05$). This may be a result of students classified as English Language Learners making greater progress (based on the teacher progress score calculation) as they acquire the English language in comparison to those classified as an ethnic minority. It may also be related to the subject area of mathematics that was the focus of this study, rather than a language arts content area. An ACT Research Report on growth patterns for English Language Learners between grades 8 and 12 also found above-average growth in mathematics for ELL students (Bassiri & Allen, 2012) when comparing the same student's performance on the ACT between grades 8 and 12.

Given that greater use of these formative assessment tools does have a positive influence on the progress scores of teachers, it was also important to determine what factors determine greater use by a teacher. The results of this analysis revealed that the more experienced a teacher, the less frequently they accessed the data (but not at a statistically significant level) for YPP. This direction of influence may be a result of more experienced teachers being less comfortable with the technology involved in using these tools. However, when considering the use of Acuity, the more experienced the teacher, the more frequently they accessed data (again not at a statistically significant level). This may be the result of more experienced teachers more consistently following a district directive to give these assessments at the designated times throughout the year.

The school-level factor of computer availability was also consistent with other research findings that the more accessible the data the more likely teachers will use it (Kerr, et al., 2006; Lachat & Smith, 2005; Luo, 2008; Marsh, et al., 2006) This study found that the greater the availability of computers at a school, the more frequently the assessments were given (but not at a statistically significant level).

Another factor from the supporting research that had a significant effect on data use was leadership at the school level. Because the administrator survey was given in the 2012-2013 school year (when only Acuity was available to teachers and principals), the resulting data from this survey were used in models considering only Acuity use as a variable. When progress scores were considered as the outcome variable and school level factors (percentage of students from ethnic minorities, percentage of English Language Learners, percentage of students with disabilities, and percentage of students who qualify for free or reduced lunch) were controlled, the leadership factor of supporting collaboration had a statistically significant influence on Acuity use ($p<0.05$). This supports previous studies that point to the importance of principal leadership in successfully using data to inform instruction (Copland, 2003; Little, 2012; Wayman, Cho, et al., 2012; Wayman, Spring, et al., 2012).

Limitations of the Study

While there are significant strengths of this study that contribute to the current body of research focused on data-driven decision making in schools, there are also limitations. This study was limited in its scope. The focus was on a single district with a small sample size (n=524) and its use of two online formative assessment systems, YPP and Acuity. Therefore, the analysis of the use of these specific data systems may be limited in its usefulness to this district and not necessarily generalizable to other districts or other educational settings. This study focused on mathematics and therefore, the results may not be generalized to other content areas. Additionally, the use of a progress score is limited in its ability to measure student achievement as there are many other variables that influence student performance.

Another limitation in this study is related to the possible assumption that more frequent use of formative data systems by classroom teachers will result in greater gains in academic achievement. While the results of this study indicated a *correlation* between frequency of formative assessments and gains in academic achievement outcomes at the teacher level, these variables are not necessarily *causal* in relationship. Furthermore, this study did not determine how the data from these assessments were used by teachers, it measured the frequency in which teachers used the systems to assess their students.

The data available for this study also created some limitations. The Acuity data use variable had a very small variation in scores. This made it difficult to ascertain meaningful results related to differences in use of this system by individual teachers. The leadership variables used were also not ideal due to the misalignment of the years during which the data were collected. The administrator survey was not given until December of 2012 and the other data on use of the data systems were collected during the previous school year, 2011-2012. This required an assumption that the administrator's support of data use was consistent across two years. It also limited the number of schools that were used in the analysis (n=32) as several principals were moved to other schools between these two school years. While the administrator survey attempted to measure constructs related to data use, it would have been valuable to also have teacher perspectives regarding these constructs. This limited the ability to triangulate data related to these data use constructs at the school level.

Considering these limitations as well as the results from this study, there are some important implications. Some of the implications of this study can inform additional research. There are also implications as a result of this study for practice in educational settings and for educational leaders.

Implications for Research

The results of this study provide an important addition to the research supporting the use of data to inform and drive instruction. This study was able to find a positive correlation between student achievement and frequency of the use of formative assessment tools using quantitative methods. However, there are components of data use that are still rather elusive in terms of identifying their effect or establishing a causal relationship to student achievement outcomes. One of the assumptions made in this study is that the more frequently teachers assess students using a data system that provides ongoing formative assessments, the more frequently they are effectively using this data to adjust their instructional practice. This assumption is what Black and Wiliam (1998) refers to as the "black box" in that we have data that enters this system, but we do not have a clear understanding of what occurs in this information loop as it interfaces with the teaching cycle. While this study considered this first step in the decision-making process as teacher access data systems, more research is needed to explore specifically how data are used by teachers to modify their instructional practices, thereby discovering what occurs in that “black box”.

This study also highlights potential differences in the types of formative assessments and their possible influence on student achievement and instructional practice. This study utilized two different vendor provided tools for assessment: YPP was used as a progress monitoring tool throughout the year, while Acuity was designed as a benchmarking tool, with prescribed periods for pre and post testing. While both of these tools have the potential to be used as formative assessment tools, further research could explore the differences in utility for teachers as they utilize different data to inform their practice. Other data sources could also be considered in future research, including common formative assessments that are frequently teacher created, informal observational data, etc.

The results of this study also provide evidence that supports the importance of leadership, specifically in providing support for collaboration at school sites. As professional learning communities become a standard part of practice in school settings, researchers are looking more specifically at what occurs in these communities to enhance instruction and effectively utilize data to drive decisions and the role of administrators in this process (Little, 2012; Moss, Brookhart, & Long, 2013; Shen, et al., 2012). There is a need for additional research to continue to identify effective ways to support this work with the overall goal of improving classroom instruction.

While this study focused on the leadership that occurs at the school level, there is also a need to understand the influence of district-level leadership on decision making that is data driven. The specific tools considered in this study (YPP and Acuity) were purchased by the district and directives for their use were given at the district administration level. This level of influence has important implications in practice and could be a direction for further research. Additionally, district leadership can also be an important component for supporting collaboration efforts at the school level and this influence is also worth further research.

Implications for Practice

The results of this study have implications for teachers and administrators in educational settings. There is a correlation between the frequency with which teachers are assessing students and a teacher's ability to make end of level progress with students. While it seems intuitive that the more a teacher is aware of progress made toward the mastery of concepts, the more targeted the instruction; the correlations found in this study provide support for this use of data as well. School leadership positively influences teacher's use of data, which in turn positively affects progress made by students on end of level assessments. Specifically supporting collaboration around data use can significantly influence a teacher's use of data. Building administrators support this in a variety of ways: providing time for collaboration, encouraging the use of data during collaboration through use of protocols and guiding questions, and the expectation that this type of data be analyzed.

As district leaders continue to look toward ways to increase student achievement, formative assessment systems will play an important role. This research supports much of the previous research in establishing the importance of having accessible data and data systems that provide formative data to guide teacher instruction. District leadership is also essential in supporting building administrators in their ability to provide opportunities for collaboration and guide teachers in their use of data. Ultimately, this classroom use of data to inform and guide instruction is where the positive outcomes for students can occur and data-driven decisions can lead to important and effective changes in education

APPENDIX

ADMINISTRATOR SURVEY

Construct	*Please indicate the degree to which you agree about the following statements (SD-Strongly Disagree, SWD –Somewhat Disagree, NDNA – Neither Disagree Nor Agree, SWA – Somewhat Agree, SA – Strongly Agree):*	*SD*	*SWD*	*ND NA*	*SWA*	*SA*
District Vision	There are clear goals for teaching and learning in my district.					
	There is a clear vision for the use of data to inform instruction in my district.					
Supportive Computer Systems	I have the proper technology to effectively examine data.					
	The computer systems in my district are user-friendly.					
	The computer systems in my district provide me access to the data I need to inform instruction.					
	The data I need to inform instruction is provided in a user-friendly format.					
Supports for Using Data	My district provides useful professional development opportunities to help me learn more about how to use data to inform instruction.					
	There is someone I can go to who can answer my questions about using data to inform instruction.					
	I have participated in professional development on the use of Acuity data to inform instruction.					
Supports for Collaboration Around Data Use	I provide professional development for the teachers in my building on the use of Acuity data to inform instruction.					
	I expect teachers in my building to review, analyze and use data from Acuity to inform instruction.					
	I encourage teachers to share strategies for using Acuity to inform instruction.					
	I designate time for teams to collaborate around data use to inform instruction.					
	I provide guiding questions or protocols for teachers to use when analyzing data.					
	The guiding questions or protocols teachers use include expectations for an end product (lesson plans, interventions, additional assessments).					
	The guiding questions or protocols teachers use include opportunities for teachers to set goals for performance on benchmark testing.					

REFERENCES

Ball, D. L., & Forzani, F. M. (2007). What makes educational research "educational"? *Educational Researcher, 36*(9), 529-540.

Bassiri, D., & Allen, J. (2012). *Grade 8 to 12 academic growth patterns for English language learners and students with disabilities*(1). Iowa City, IA: ACT.

Black, P., & Wiliam, D. (1998). Inside the black box: Raising standards through classroom assessment. *Phi Delta Kappan, 80*(2), 139-144, 146-148.

Blanc, S., Christman, J. B., Liu, R., Mitchell, C., Travers, E., & Bulkley, K. E. (2010). Learning to learn from data: Benchmarks and instructional communities. *Peabody Journal of Education, 85*(2), 205-225.

Breiter, A., & Light, D. (2006). Data for school improvement: Factors for designing effective information systems to support decision-making in schools. *Educational Technology & Society, 9*(3), 206-217.

Brunner, C., Fasca, C., Heinze, J., Honey, M., Light, D., Mandinach, E., et al. (2005). Linking data and learning: The grow network study. *Journal of Education for Students Placed at Risk, 10*(3), 241-267.

Chrispeels, J. H., Castillo, S., & Brown, J. (2000). School leadership teams: A process model of team development. *School Effectiveness & School Improvement, 11*(1), 20-56.

Clark, I. (2011). Formative assessment: Policy, perspectives and practice. *Florida Journal of Educational Administration and Policy, 4*(2), 158-180.

Coburn, C. E., & Talbert, J. E. (2006). Conceptions of evidence use in school districts: Mapping the terrain. *American Journal of Education, 112*(4), 469-495.

Cohen, D. K., Raudenbush, S. W., & Ball, D. L. (2003). Resources, instruction, and research. *Educational Evaluation and Policy Analysis, 25*(2), 119-142.

Collinson, V., Cook, T. F., & Conley, S. (2006). Organizational learning in schools and school systems: Improving learning, teaching, and leading. *Theory Into Practice, 45*(2), 107-116.

Copland, M. A. (2003). Leadership of inquiry: Building and sustaining capacity for school improvement. *Educational Evaluation and Policy Analysis, 25*(4), 375-395.

Datnow, A., Park, V., & Wohlstetter, P. (2007). *Achieving with data: How high-performing school systems use data to improve instruction for elementary students*. Los Angeles, CA: Center on Educational Governance.

Faria, A.-M., Heppen, J., Li, Y., Stachel, S., Jones, W., Sawyer, K., et al. (2012). *Charting success: Data use and student achievement in urban schools*. Washington, DC: Council of the Great City Schools.

Gallagher, C., & Worth, P. (2008). *Formative assessment policies, programs, and practices in the Southwest Region* (No. REL 2008-No. 041). Washington, D.C.: Institute of Education Sciences, National Center for Education Evaluation and Regional Assistance, Regional Educational Laboratory Southwest.

Gallagher, L., Means, B., & Padilla, C. (2008). *Teachers' use of student data systems to improve instruction: 2005 to 2007.* Jessup, MD: US Department of Education.

A Guide to U-PASS Determinations. (2008). Retrieved from www.schools.utah.gov.

Halverson, R., Grigg, J., Prichett, R., & Thomas, C. (2007). The new instructional leadership: Creating data-driven instructional systems in school. *Journal of School Leadership, 17*(2), 159-194.

Hayes, A. F. (2006). A primer on multilevel modeling. *Human Communication Research, 32*, 385-410.

Heritage, M., & Chen, E. (2005). Why data skills matter in school improvement. *Phi Delta Kappan, 86*(9), 707-710.

Heritage, M., Kim, J., Vendlinski, T., & Herman, J. (2009). From evidence to action: A seamless process in formative assessment? *Educational Measurement: Issues and Practice, 28*(3), 24-31.

Herman, J., & Gribbons, B. (2001). *Lessons learned in using data to support school inquiry and continuous improvement: Final report to the Stuart Foundation* (No. CSE Technical Report 535). Los Angeles, CA: University of California.

Honig, M. I., & Coburn, C. (2008). Evidence-based decision making in school district central offices: Toward a policy and research agenda. *Educational Policy, 22*(4), 578-608.

Ingram, D., Louis, K. S., & Schroeder, R. G. (2004). Accountability policies and teacher decision making: Barriers to the use of data to improve practice. *Teachers College Record, 106*(6), 1258-1287.

Kerr, K. A., Marsh, J. A., Ikemoto, G. S., Darilek, H., & Barney, H. (2006). Strategies to promote data use for instructional improvement: Actions, outcomes, and lessons from three urban districts. *American Journal of Education, 112*(4), 496-520.

Kowalski, T. J. (2009). Evidence and decision making in professions. In T. J. Kowalski & T. J. I. Lasley (Eds.), *Handbook of data-based decision making in education* (pp. 3-19). New York, NY: Routledge.

Lachat, M. A., & Smith, S. (2005). Practices that support data use in urban high schools. *Journal of Education for Students Placed at Risk, 10*(3), 333-349.

Little, J. W. (2012). Understanding data use practice among teachers: The contribution of micro-process studies. *American Journal of Education, 118*(2), 143-166.

Luo, M. (2008). Structural equation modeling for high school principals' data-driven decision making: An analysis of information use environments. *Educational Administration Quarterly, 44*(5), 603-634.

Marsh, J. A., Pane, J. F., & Hamilton, L. S. (2006). *Making sense of data-driven decision making in education: Evidence from recent RAND research*. Santa Monica, CA: RAND Education.

Moss, C. M., Brookhart, S. M., & Long, B. A. (2013). Administrators' roles in helping teachers use formative assessment information. *Applied Measurement in Education, 26*, 206-218.

Randel, B., Beesley, A. D., Apthrop, H., Clark, T. F., Wang, X., Cicchinelli, L. F., et al. (2011). *Classroom assessment for student learning: The impact on elementary school mathematics in the Central Region* (No. NCEE 2011-4005). Washington, D.C.: National Center for Education, Evaluation and Regional Assistance, Institute of Education Sciences.

Raudenbush, S. W., & Bryk, A. S. (2002). *Heirarchical linear models: Applications and data analysis methods* (2nd ed.). Thousand Oaks, CA: Sage Publications.

Schildkamp, K., & Kuiper, W. (2010). Data-informed curriculum reform: Which data, what purposes, and promoting and hindering factors. *Teaching and Teacher Education: An International Journal of Research and Studies, 26*(3), 482-496.

Shen, J., Cooley, V. E., Xin, M., Reeves, P. L., Burt, W. L., Rainey, M., et al. (2012). Data-informed decision making on high-impact strategies: Developing and validating an instrument for principals. *The Journal of Experimental Education, 80*(1), 1-25.

Stecker, P. M., Fuchs, L. S., & Fuchs, D. (2005). Using curriculum-based measurement to improve student achievement: Review of research. *Psychology in the Schools, 42*(8), 795-819.

Symonds, K. W. (2004). *After the test: Closing the achievement gaps with data*. Naperville, IL: Learning Point Associates.

Volante, L., & Cherubini, L. (2009). *How teachers and school administrators connect large-scale assessment with school improvement planning*. Paper presented at the Annual Meeting of the American Educational Research Association. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=eric&AN=ED509794&site=ehost-live

Wayman, J. C. (2005). Involving teachers in data-driven decision making: Using computer data systems to support teacher inquiry and reflection. *Journal of Education for Students Placed at Risk, 10*(3), 295-308.

Wayman, J. C., Cho, V., Jimerson, J. B., & Spikes, D. D. (2012). District-wide effects on data use in the classroom. *Education Policy Analysis Archives, 20*(25).

Wayman, J. C., Cho, V., & Johnston, M. T. (2007). *The data-informed district: A district-wide evaluation of data use in the Natrona County School District*. Austin, TX: The University of Texas.

Wayman, J. C., Spring, S. D., Lemke, M. A., & Lehr, M. D. (2012). *Using data to inform practice: Effective principal leadership strategies*. Paper presented at the American Educational Research Association. Retrieved from http://www.waymandatause.com/wp-content/uploads/2013/11/Wayman-Spring-Lemke-Lehr-Principal-Data-Use-Strategies.pdf

Young, V. K., & Kim, D. H. (2010). Using assessments for instructional improvement: A literature review. Retrieved from Educational Policy Analysis Archives website: http://epaa.asu.edu/ojs/article/view/809

Ysseldyke, J., & Tardrew, T. (2007). Use of progress monitoring system to enable teachers to differentiate mathematics instruction. *Journal of Applied School Psychology, 24*(1), 1-28.